Modelling the spatial energy diversity in sub-city areas using remote sensors

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ABSTRACT

This research paper aims first to present in a digital map a class information about surface temperature in domestic buildings by means of thermal imagery. The classes are relative to the particular temperature distribution and for the particular night of the survey. Classification assigns every pixel into one of five classes based on where the pixel falls in the histogram, into an integer between 1 and 5, with 1 representing being the "coolest" pixels and 5 being the "hottest" resolution, based on a case study acquired over Newcastle upon Tyne (United Kingdom). The ultimate aim is combine this information with building level data set for Newcastle and adds on the energy modelling aspect through linking with the English House Survey (EHS) as input to the Cambridge Housing Model (CHM). This provides the means to produce building level energy use estimates and surface temperature, which in turn can be analysed both spatially and aspatially. This building level approach provides the potential for energy planners and other bodies to model energy interventions measures with flexibility in scale and to potentially adapt plans to the spatial variability of the local area characteristics.

Keywords

Energy use;
Microclimates;
Surface temperature;
Thermal images;
Urban energy modelling.

1. Introduction

European building stock is highly diverse, particularly in local and regional places where there exists complex building forms affecting energy use; for example, in Newcastle upon Tyne United Kingdom (UK), there is a high proportion of bed-sits (bed-sits are not considered as a dwelling type in English House Survey) and regional building types, like the North East Tyneside flat, forming part of a terrace and horizontally divided as a semi-detached buildings. Tyneside flats have a usable floor area that is below the UK average and so it is difficult to impute values from other national data sets. Additionally, some of the worst problems in the housing condition are focalized in the inner core terraces as well as the outer estates, often where not so popular stock types (detached, maisonettes and one-bed old people's units) interact with high fuel poverty areas. In Newcastle, an area-based approach would allow more houses to be targeted in places where local area characteristics show energy inefficient elements, and may therefore potentially capture a greater number of fuel poor households per unit of cost. New governance mechanisms, such as the Local Strategic Partnerships [1] , envisage an important role for area-based initiatives, which have a major impact on deprived areas (e.g. Newcastle West End is included as one of the six case studies). Also, Newcastle is one of the nine areas in the Housing Market Renewal Pathfinders [2] where "demand for housing is relatively weak; areas which have seen a significant decline in population, dereliction, poor services and poor social conditions". The basis of the Pathfinder Housing Market Renewal programme in Newcastle is a robust evidential base for making programme decisions in which the importance of quantitative information (explicitly including understanding energy use) or 'drivers' for informing strategic interventions in the housing market has been established as one of the aspects of any assessment. This study aims to contribute to this evidence by estimating the energy use in sub-city areas through a bottom-up framework strategy. Furthermore, our framework would allow us to pose some questions about appropriate retrofit measures [3] in Newcastle and other matters related to energy use.

The use of remote sensors and geographic information systems allowed the study of the urban spatial variability for different applications. Examples include: Oloo et al. [4] who assesses the potential of photovoltaic solar spatial variability of urban solar energy potentials in Kenya. Tomc and Vasallo [5] use a business model in which the technology and social aspects are approached in a transdisciplinary manner, and Torre-Tojal et al. [6] estimate aboveground biomass in Spain using exclusively public and accessible

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data from Light Detection and Ranging (LiDAR) flights. Our research uses a thermal image and an engineering model to assess the spatial variability of domestic energy use in the United Kingdom neighbourhoods'.

This paper argues that an area-based approach allows more houses to be targeted compared to the existing self-referral method, like the Green Deal (The Green Deal scheme provides finance to make energy-saving improvements in a home and finds the best way to pay for them). The Green Deal scheme would be more appealing to the owner-occupied sector [7] if additional energy efficiency measures could be bundled into a house renovation plan. As an example of acceptance, by 31st December 2013 [8] 129,842 Green Deal scheme assessments had been made in Great Britain, of which 75% of the valid assessments were on owner-occupied properties. The relevant improvements recommended were boiler (upgrade) (13.2%), cavity wall insulation (13.2%), loft insulation (15%), micro generation (16.2%), and solid cladding (10.6%), and usually two to three improvements were recommended per assessment.

Regionally, the number of assessments in the North East were low, as from 3,976 (3.06% of the total) only 280 (0.22% of the total) were made in Newcastle upon Tyne. The number of live Green Deal plans in Newcastle was only four out of 100 in Great Britain. The provisional number of properties with energy efficiency work delivered under Core Cities Project in Newcastle was only 137, with the number of measures installed being 312.

This paper uses an innovative area-based approach for mapping and monitoring heat loss from a group of buildings using imagery from an airborne thermal remote sensing and a building-based energy use framework to reduce energy use. This paper focuses on a hitherto unexplored research question, for which at present there is no definitive answer, which in essence relate primarily to the influence of local area characteristics like green areas, clustering of settlements etc. as influencing parameters on specific energy use in buildings. This information can be used by local governments to identify areas for future intervention, and thus enhance the effectiveness of energy efficiency policies and measures.

2. Approaches for reducing the energy use

In the United Kingdom, the approach to reduce energy use is to identify which measure and its combinations i.e. the building fabric and energy supply systems that are capable of making a significant contribution and the marginal value in the available policies and technologies. Shorrock and Utley [9] estimate that in Britain the overall heat loss of the average dwelling was reduced approximately by 31% between 1970 and 2001. Figure 1 shows the contributions of various building fabric elements to the heat loss of the average dwelling. Heat loss is measured in either kilowatts (kW) or British Thermal Units (BTUs). U-values [10] are used to measure how effective elements of a building's fabric are at insulating against heat loss. The lower the U-value of a building's fabric, the less energy is required to maintain comfortable conditions inside the building. The buildings regulations set out the limiting standards for the properties of the fabric elements of the building [11], described in terms of maximum U-values. Usually, an older a building is susceptible to heat loss as older buildings are constructed to lower thermal standards (e.g. using solid walls, unfilled cavity wall, and single glazing) than modern buildings [12].

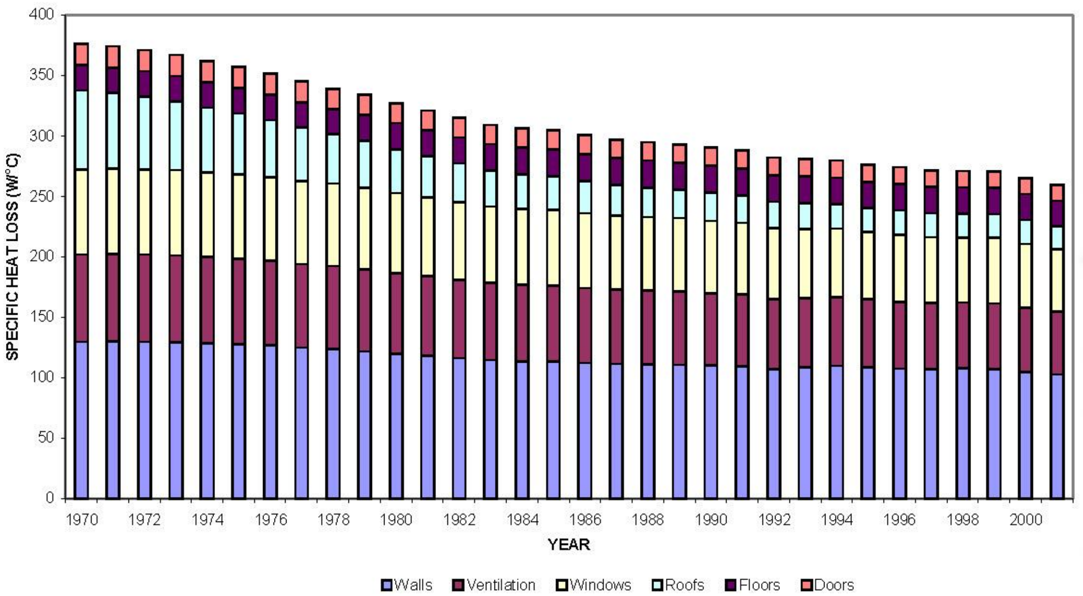


Figure 1 Heat loss of the average dwelling (Based on [9])

Figure 1 shows that the mean heat loss has fallen approximately by 115 W/K in the average house, and approximately 40% reduction is in insulation of roofs. Also in Figure 1, there is a small reduction in walls, windows and ventilation (mainly air leaking) by 2001 presumably to the fact that most walls (solid or cavity) remain uninsulated and there is a significant housing stock with single glazing in windows. We argue that an interesting application of thermal remote sensing is detecting and monitoring heat loss from buildings in urban areas i.e. area-based sites targeted for repair and re-insulate the building envelope so to conserve energy.

Airborne thermal infrared sensors are widely used for military applications, later advances in the sensor technology made them available for remote sensing tasks in cities. Thermal sensors employ one or more internal temperature references for comparison with the detected radiation, so they can be related to absolute radiant temperature. Airborne thermal remote sensing is an attractive option for identifying areas of high surface heat exposure. Airborne thermal remote sensing gives an excellent spatial picture of the urban landscape for a snapshot in time, allowing a comparative analysis of areas of high surface temperatures. The advantage of airborne thermal remote sensing is the ability to observe high resolution surface temperatures, allowing the identification and analysis of individual landscape elements, therefore to relate surface temperatures to different land surface building types and features, and also have demonstrated that vegetation cover and urban geometries are important controls of surface temperatures. However, for most of the thermal remote sensing data, other auxiliary data can be accessed to assist in processing, analysing and interpreting the imagery, like estimations of energy use per building. Correlations between surface temperature and energy reductions would help to further understand the role of building features in urban domestic sector. In this paper a measure of the waste heat at different temperatures is then analysed and coloured maps are produced for buildings areas.

For energy use estimations of individual buildings, we use the Newcastle Carbon Route Framework (NCRF) [13, 14]. NCRF is a building-based energy framework comprised of city-wide individualized spatial per-dwelling records in a PostGIS™ spatial database, which later were imported to an ESRI geo-database for further spatial analysis. Every spatial per-dwelling record is keyed on the Unique Topographic Identifier (TOID), a TOID is a unique reference identifier associated with every building within Ordnance Survey's (OS) large scale topographic mapping and associated with their Unique Property Reference Number (UPRN). This allows a common set of attributes to be displayed as either the building outlines or the property parcels identified in the UPRN.

This study uses the Cambridge Housing Model (CHM) which implements a Building Research Establishment Domestic Energy Model (BREDEM) based energy model to compute energy estimates as it is the model used by DECC to underpin the 2012 Housing Energy Fact File and Energy Consumption in the UK [15]. The calculations used in the CHM are principally based on the Standard Assessment Procedure (SAP) 2009 [10]. SAP 2009 is the latest interpretation of the most widely-tested and widely-used framework for assessing energy use in UK homes, the BREDEM version 12 [16]. BREDEM-12 uses both analytical and empirical approaches, the analytical being a balancing equation for heat losses against gains in dwellings. This equation incorporates empirical functions to estimate the utilisation of gains, demand for hot water, and the energy use for cooking, lights and appliances. The information required to perform a BREDEM calculation is: (i) Site definition; (ii) Type of Dwelling; (iii) Building Fabric; (iv) Ventilation; (v) Heating Systems; (vi) Hot water heating; (vi) Mechanical Ventilation (if present); (vii) Cooking; (viii) Lightning; (ix) Occupancy; (x) Conservatory (if present and unheated) [16]. This energy use process creates individual energy use estimates for each dwelling and aggregates these to sub-city areas. The process utilise a physic based approach to energy modelling based on BREDEM 12 methodology [15]. It was decided that the best BREDEM-like model to adopt for this investigation is the Cambridge Housing Model (CHM); the calculations in the CHM are principally based on the worksheet in SAP 2009, the Government's Standard Assessment Procedure for energy rating of dwellings, plus the Reduced Data SAP (RDSAP) for existing dwellings [17]. The SAP 2009 outputs for energy use and associated CO_2 emissions do not include cooking or electrical appliances. CHM has therefore included calculations for energy use for cooking and electrical appliances, and associated CO_2 emissions, based on the Building Research Establishment Domestic Energy Model (BREDEM-8) and SAP. However, our framework approach could be applied to any other energy model.

The most disaggregated level of spatial information in NCRF is about a single dwelling. The dwelling has a unique property identifier (its UPRN code) and the address information; both are part of the Local Land and Property Gazetteer (LLPG) and the aggregated National Land and Property Gazetteer (NLPG) data set. Local authorities in UK have statutory responsibility for the street name and property number (LAs are involved in all stages of the property lifecycle –planning, building, occupation and demolition) and additionally inform Royal Mail of new buildings and address changes. NLPG data set is made up from each of the constituent LLPGs, and also joined-up (characterized by coordination and coherence of though) national (local and national statistics, social services, and others) and regional services (Highways, counties, ambulance, fire, and police) [18]. Gazetteer refers to those records in the data set where attributes have been added through incorporation of the LLPG records. The next level of hierarchy corresponds to a building as a building could have a number of dwellings. Every building is identified by a TOID. At the building level, two additional information were integrated: The Cities Revealed (CR) data (CR refers to those records in the data set where attributes have been added through incorporation of the Cities Revealed records) enables us to identify all residential properties by age and structure category through the Cities Revealed building class code compatible with Ordnance Survey Mastermap™ data [19]. The building Class provides a detailed perspective of the built environment, see Figure 2. The Cities Revealed building classification data set provides building classifications and ages against MasterMap™

building outlines. In addition a further set of building classifications were incorporated showing building use classification from the Sustainable Cities: Options for Responding to Climate Change Impacts and Outcomes (SCORCHIO) project [20] (SCORCHIO refers to those records in the data set where attributes have been added through incorporation of the SCORCHIO records) that identifies the number of residential and commercial properties within the building. Figure 4 shows a detailed account of the data sets in this paper.

IMAGE TO INFORMATION

BUILDING CLASS REFERENCE SHEET

TYPE	AGE	Historic to end Georgian -1837	Early and Middle Victorian 1837-1870	Late Victorian/ Edwardian 1870-1914	World War 1 - World War 2 1914-1945	Post war regeneration 1945-1964	Sixties/ seventies 1964-1979	Recent years 1979-photo date
		1	2	3	4	5	6	7
Very Tall Flats (point blocks)	1					55	74	93
Tall flats 6-15 storeys (slabs)	2					56	75	94
Medium height flats 5-6 storeys	3			25	40	57	76	95
Lower 3-4 storey and smaller flats, detached and linked	4			26	41	58	77	96
Tall terraces 3-4 storeys	5	2	13	27	42	59	78	97
Low terraces, 2 storeys with large T-rear extension	6	3	14	28	43	60	79	98
Low terraces, small	7	4	15	29	44	61	80	99
Linked and step linked houses, 2-3 or mixed 2 and 3 storeys	8					62	81	100
Planned balanced-mixed estates	9					63	82	101
Standard size semis	10	5	16	30	45	64	83	102
Semi type house in multiples of 4,6,8 etc.	11			31	46	65	84	103
Large property semis	12	6	17	32	47	66	85	104
Smaller detached houses	13	7	18	33	48	67	86	105
Large detached houses	14	8	19	34	49	68	87	106
Very large detached houses, sometime now flats	15	9	20	35	50	69	88	107
Non residential building	16							132
Residential building - Unknown classification	17							333
Domestic Shed or Out-building	18							555

Figure 2 Cities Revealed Building Class reference sheet

The initial data set was cleaned and restructured for this study and additional data layers were integrated. The LA provided dwelling level information about the social housing through the Your Home Newcastle (YHN) data. YHN [21] is an Arm's Length Management Organization (ALMO) responsible for managing council homes on behalf of Newcastle City Council. In 2009 YHN managed 28,950 council homes on behalf of Newcastle City Council, 1,800 homes on behalf of the Byker Community Trust and 330 homes on behalf of Leazes Homes. YHN also manage 1,500 leasehold properties on behalf of Newcastle City Council and the Byker Community Trust. YHN refers to those records in the data set where attributes have been added through incorporation of the YHN records. Calderon et al. [22] provides the details of the major data sets used to create the data as part of this study.

YHN council homes have an accurate build date taken from the deeds. YHN properties mainly consist of post-war, non-traditional buildings; however there are also a large number of pre-1919 terraces, semi-detached and flats in their housing stock. Where possible, NCRM YHN dates were used in preference to other building age data as it was deemed the most reliable. The additional attributes provided by the YHN records for 28,950 properties were added to the NCRM data set as part of this study.

An example of the problems faced in fusing multiple data sets is the building type classifications, of which WarmZone, Cities Revealed, LA Gazetteer and YHN all had different categories. In many cases this required looking for building market information or a small scale field work in order to map between categories consistently. A similar problem was found in building age classifications and categories which did not align perfectly and needed mappings to be created between categories. In the last four years, this paper found interesting research using the spatial diversity approach. Examples are Grafius et al. [23] who argue that in modelling ecosystem services an optimal balance must be sought between feasibility and capability i.e. a balance is important between scarce and detailed data. Reinhart and Cerezo [24] who argue that city-wide Geographic Information Systems (GIS) are increasingly accessible to the general public combined with LiDAR data or building heights as well as open semantic formats such as CityGML and used to generate extruded models of whole cities. In the UK, the Cambridge University [25] Energy Efficiency in Cities initiative (EECi) uses a bottom up' tool that brings together detailed data, expert knowledge, and energy simulation, the goal is to strengthen the UK's capacity to address energy demand reduction in cities. This paper proposes remote sensing techniques in conjunction with results from more rigorous building energy modelling framework to show the possible association between land use/land cover patterns on surface temperature and energy use in buildings at different scales.

Although the terms land use and land cover have been used interchangeably, it is important to remember that the two expression are not necessary synonymous. Land use [26-28] encompasses several aspects of people's relationship to the environment. By comparison, land cover [29-31] is represented by the natural and artificial compositions covering the earth surface at certain location. Land use is a cultural concept that describes human activities and their use of land, whereas land cover is a physical description of land surface [32]. Land cover can be used to infer land use, but the two concepts are not entirely interchangeable, as an example, Guérois and Pumain [33] use CORINE land cover classifications to derive built-up densifications and their evolution over time.

Thermal images allow to qualitatively observing ventilation leaks [34], conduction losses and thermal bridging [35]; defective services [36]; moisture condensation [37]; moisture ingress [38]; structural defects [39]; quantitative energy performance measurement [40]. Benefits include identifying problems without needing to gain access to buildings and being able to observe problems on large buildings more efficiently. Stockton [41] argue on such an application and finding show that aerial thermal images are well placed for detecting moisture over flat roof surfaces. Others suggest how aerial thermal images could be used quantitatively to determine energy loss from roofs [42], however limitations to this methodology such as roof shape & pitch, image blurring, internal temperatures, climate and emissivity could impact on and require consideration of for qualitative analysis [43]. A clear limitation to this methodology is that it does not seem possible to observe wall or fenestration defects, since these have not been reported on and could be due to the height and parallel angle of the camera from the plane to the building.

Urban areas tend to have higher air temperatures than their rural surroundings, as a result of gradual surface modifications that include replacing the natural vegetation with buildings and roads. This is because vegetation plays a significant role in regulating the urban microclimate and can influence domestic energy demand through solar absorption and the cooling effects provided by shade and evapotranspiration (Akbari et al. [44] and Akbari and Konopacki [45]). This may mean that areas with a low residential density indicative of more open space require more energy to maintain the same temperature as higher density areas.

3. Modelling the spatial diversity

This paper has selected Castle, a Middle Layer Super Output Area (MLSOA) in the United Kingdom for the analysis. Castle is a low residential density MLSOA, which means the effects of microclimates are likely to be more influential than in high density areas (due to the urban heat island effect) meaning energy use is likely to be higher than the average. For a thorough explanation of how vegetation affect microclimates and the energy use see [46], [44] and [45]; and for quantification, one possible interpretation mechanism is from thermal images. The methodology is summarized in Figure 3.

The initial variables of the individual dwelling energy profile are: usable floor area, dwelling type, construction date, number of floors above ground, predominant type of wall structure, cavity wall insulation, main heating fuel, primary heating system, boiler group and tenure.

This study uses record generation algorithms (see Figure 3) with the sub-city CRM complete ten-variable records data set in the three case study areas (Castle, South Heaton and Westgate) to obtain complete coverage in the corresponding MLSOAs areas. The Inverse Distance Weighting (IDW) algorithm was used in Castle because dwellings show a cluster distribution, while the nearest neighbour (NN) was used in South Heaton because dwellings show a uniform distribution. Stochastic Kriging was used in Westgate because it has one of the most diverse collections of building classes (including tower blocks buildings) in the Newcastle area.

This study uses secondary data sets from Arms' Length Management Organizations (ALMO) to gather rented and leased social housing characteristics and specific data on energy systems. The research utilised the NCRM Registered Social Landlords housing information and HMO licensing from the LA, and shared housing data from Housing Associations and the LA, to understand dwellings in group heating schemes, dwellings with an Economy 7 tariff, and the number and characteristics of residential dwellings sharing district heat schemes. The interpolated data are compared with accurate detailed city information, and in the case of discrepancy city records correct the interpolated values are corrected, i.e. the sub-city DEM model data set is refined.

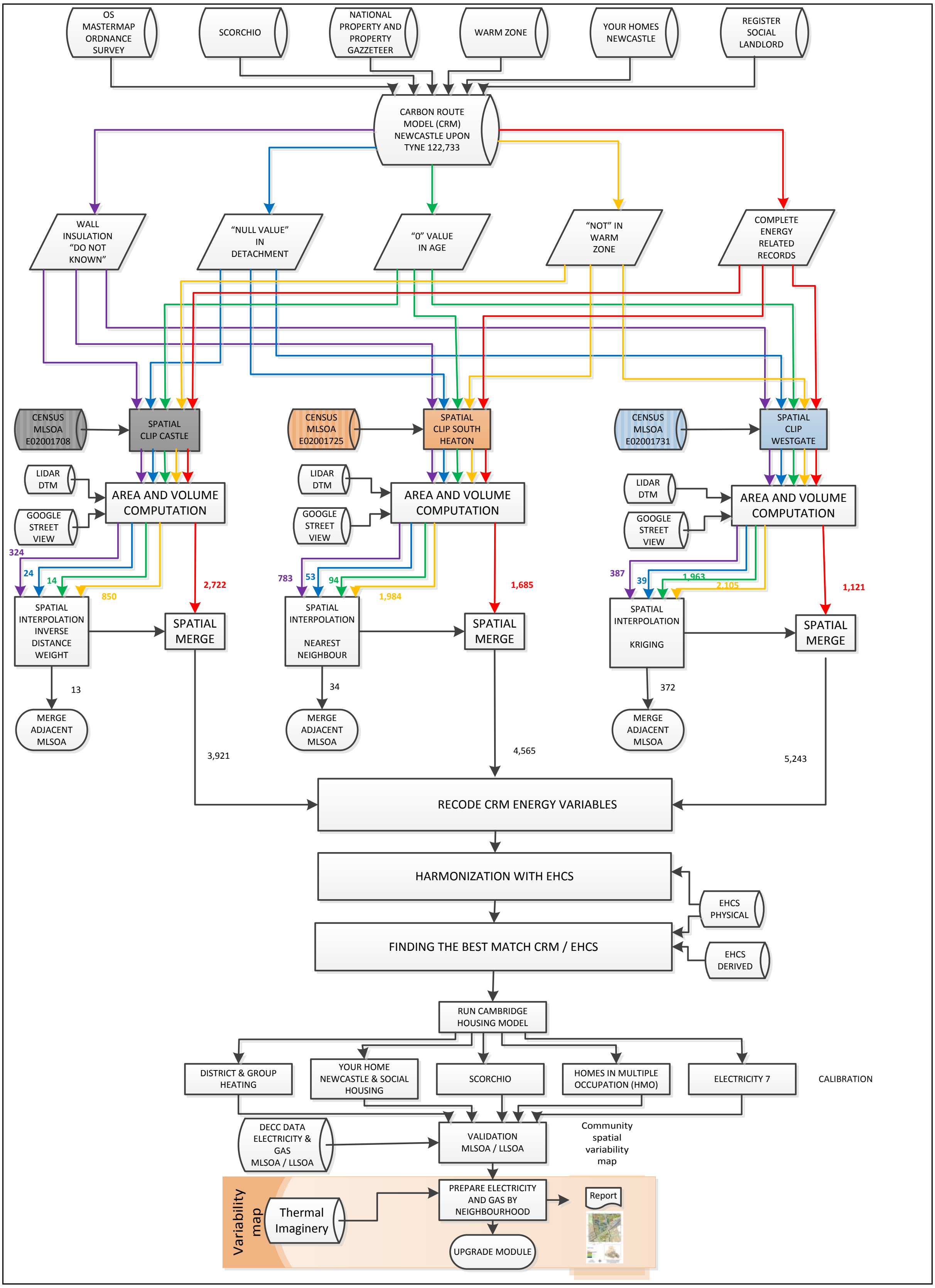


Figure 3 Variablility framework with energy measures

To cope with the fields missing in the CRM record (to obtain a full SAP record); this study has used an imputed method as an algorithm for record augmentation (see Figure 3). In our augmentation strategy the two data sets are from different geographies. NCRM cluster prototype (the acceptor) is a local data set and EHS (the donor) is a national data set. The complete data set is now called Newcastle CarbonRouteMap Framework. NCRF

NCRF spatial detailed data sets have both spatial and attribute information, and enable the analysis of detailed form and relationships. They are also sufficiently extensive to enable patterns [47] to be generalised across sub-city areas. It is increasingly possible to link the socio-economic focus of geographical analysis to the geometric built environment approach [48] that is employed in local urban planning. Batty [49] has termed this link as "geography of the third dimension to geometry", that is, the merging of iconic and symbolic urban models [50], and it opens up many possibilities for research.

Ong [51] argues that the primary cause of heat build-up in cities is insulation, the absorption of solar radiation by roads and buildings in the city and the storage of this heat in the building material and its subsequent re-radiation. Akbari, Pomerantz [44] argue that the uses of 'cool' surfaces, that is surfaces with a high albedo or reflective index, as well as planted surfaces are effective in reducing heat build-up. Plants also play a significant role in regulating the urban microclimate and can influence domestic energy demand through solar absorption and the cooling effects provided by shade and evapotranspiration, therefore more energy is demanded for maintaining the same internal temperature in the building. Additionally, all Castle Lower Layer Super Output Areas (LLSOAs) do not make the threshold (plot ratio of at least 0.3) were Directive 2012/27/EU [52] considers district heating directly feasible. Interestingly, Persson and Werner [53] classify areas based on plot ratio: plot ratio ≥ 0.5 as inner city areas, 0.3 ≤ plot ratio < 0.5 as outer city areas, and plot ratio < 0.3 as park areas and argue that "widely distributed park area settlements may prove unfeasible for district heating expansions, due to insufficient Linear Heat Density". The microclimate is an important element not considered in energy modelling. Indeed, as an example, in the Cambridge Housing Model (Hughes CHM [15]), the only climate variable used is regionally based and the value is the same for the entire North East England in terms of Monthly External Temperature (ºC); monthly Average Wind Speed (m/s); and monthly Average Horizontal Solar Radiation (W/m^2).

This paper uses the estimated energy use in Calderon et al. [13] for repeated property types by samples due that the Department of Energy and Climate Change (DECC) [54]. The Energy Act 2011 included provisions for the Green Deal. An Energy Company Obligation (ECO) integrated with the Green Deal, allows subsidy and Green Deal Finance to come together into one seamless offer. In this way, the Green Deal and the ECO will work in combination to drive the installation of energy efficiency improvements (the term used in the Green Deal legal framework to describe the installation of a measure in a property), often referred to as measures (generic energy efficiency improvements which can be made to a property, for example, loft insulation, cavity wall insulation or a replacement boiler).The Energy Act 2011 also made clear that the Green Deal may cover measures which generate renewable energy in a cost-effective way. For example, micro generation will use renewable sources of energy (such as the air, sun and ground heat) to generate energy and this ultimately results in fuel bill savings. Under the Green Deal households are always protected by the Golden Rule (the Golden Rule means the charge attached to the energy meter in a property cannot be higher than the estimated savings for the package of measures in that property).

Cambridge Architectural Research's CAR [55] expert knowledge created a database containing the maximum possible percentage for each building type to adopt a particular technology. This was based on building parameters, assumptions about which homes could adopt the technology, and the likely occupants of the building type. We created our own flowchart (see Figure 4) to communicate this knowledge and simplify decision making, and to help readers better understand the upgrades. We included in Figure 4 an indication of the maximum realistic uptake of upgrades, based on upgrading existing homes. In this paper we developed a spatially enabled database to estimate energy use in a multi-scale approach, therefore it is straightforward to set up a scenario that shows the effect of one or more upgrades to the Newcastle homes. Additionally, it is possible to define the proportion of homes to upgrade based on the precise spatial extent of the energy use in sub-city areas and develop a reverse lookup procedure that allows the identification of building aggregated areas with spatial expression patterns most similar to a given parameter within the building energy profile that might be upgraded [56]. There are forty five measures or areas of home approved to receive funding under the Green Deal, see Figure 4.

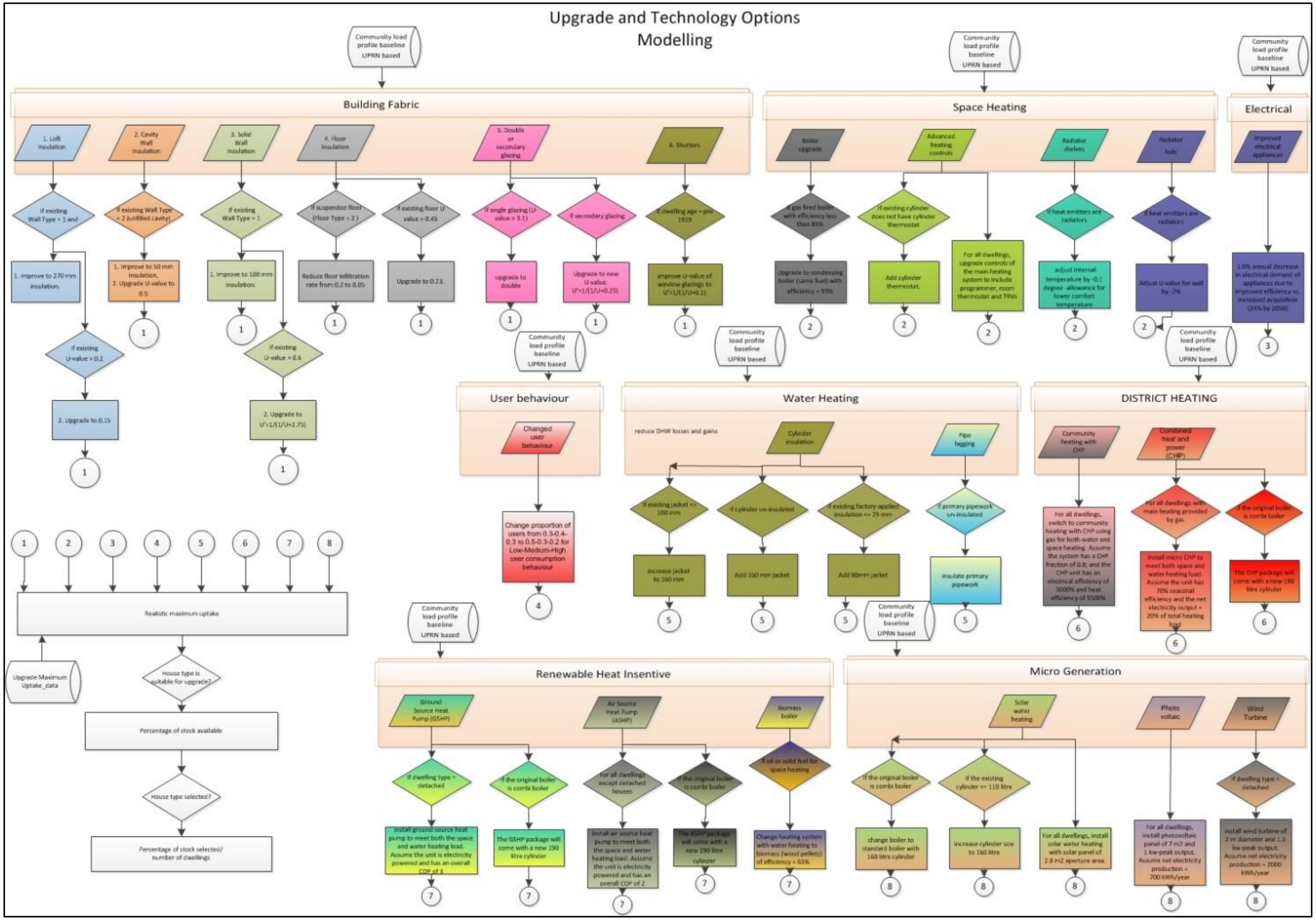


Figure 4 Modelling the upgrade and technology options

This paper groups those measures in seven functional categories, for modelling purposes, covering improvements in (i) the building fabric; (ii) space heating; (iii) electric; (iv) water heating; (v) community heating- CHP; (vi) heat from the earth, the air and newly dead biological matter burn in a boiler , and (vii) micro generation as shown in Figure 4, and also included a change in the proportion in user behaviour and electric lightning in time as measures.
The imagery (IR) from aerial thermal surveys of cities can be used to monitor by looking at surface temperatures/patterns [57]. Leaks and insulation failure in a building can result in less than optimal energy efficiency and heat losses. Despite their limitations in technical precision and cost [58], we argue that thermal imaging is an opportunity to identify and address building envelope deficiencies and promote upgrades. Psychology literature [59] suggests that the visual nature of thermal images is important in motivating viewers to action. Thermal images render invisible heat visible, thereby presenting visual evidence of areas of heat loss and potential efficiency gains.
The classification method assigns every pixel in the thermal image into one of five classes based on where the pixel falls in the histogram, into an integer between 1 and 5, with 1 representing being the "coolest" pixels and 5 being the "hottest". The resulting average pixel value for each building fails to represent the true heat loss code for that building as this can be distorted by small area high heat loss sources, e.g. chimneys etc. This is represented as another attribute in the spatially enabled database.
We include information thermal image information of the heated roof of individual buildings in Newcastle to the NCRF spatially enabled database. This provides high resolution urban variability spatial scenarios of individual building energy profiles, urban forms and land use that comprise the basis for analysis of energy use impacts at different scales. NCRF provides the flexibility to test very wide energy use measure impacts under a number of scenarios of DECC energy consumption statistics for built-up areas (MLSOAs and LLSOAs), and census data sets for the same areas are allocated on a best-fit basis using a population weighted centroid method.

4. Results

DECC, as part of the implementation and monitoring of local energy strategies, reports estimates of electricity and gas consumption data at various scales below local authority (LA) level. DECC reports individual dwelling energy consumption in the National Energy Efficiency Database (NEED) as part of the energy efficiency statistics, and aggregated dwelling energy consumption in the sub-national energy consumption statistics. Aggregated data are in two geographic areas: Middle Layer Super Output Area (MLSOA) and Lower Layer Super Output Area (LLSOA).
DECC NEED data provides values for regional based gas energy consumption across property types only. Hence, when comparing NCRF outputs to NEED data only gas consumption estimates are used. At this level, retrofit decisions can be made, whether to improve the efficiency of the supply side technologies, or invest in demand side technologies with the intention of reducing primary energy requirements. Residential building retrofits are at the forefront of the sustainable development agenda if government building regulation is taken as a proxy.
Initially, this paper compares the NCRF results with National Energy Efficiency Database (NEED) data at the sample level. The rationale behind this is to evidence how local characteristics affect the energy efficiency of individual dwellings, which in turn influence the mean and median of the whole sample, which is shown to differ significantly from the NEED values for North East England.
Figure 5 shows annual energy use (in kWh) data for repeated property types as a skewed distribution. Then, for comparative purposes, it is preferable to provide additionally to the mean and the median: (i) two outer centiles, such as the tenth and 90^{th}; (ii) the first and third quartiles (25^{th} and 75^{th} centiles) that define the interquartile range, and (iii) the range of the sample, usually the fifth centile and the 95^{th} centile, which is called the reference range 5%-95%, and is the difference between the two most extreme values. As an example, Figure 5 shows the colour and shape pattern to a skew distribution.

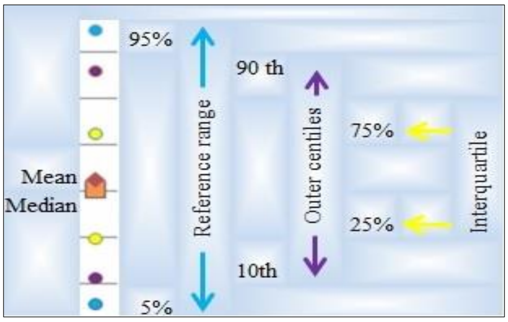
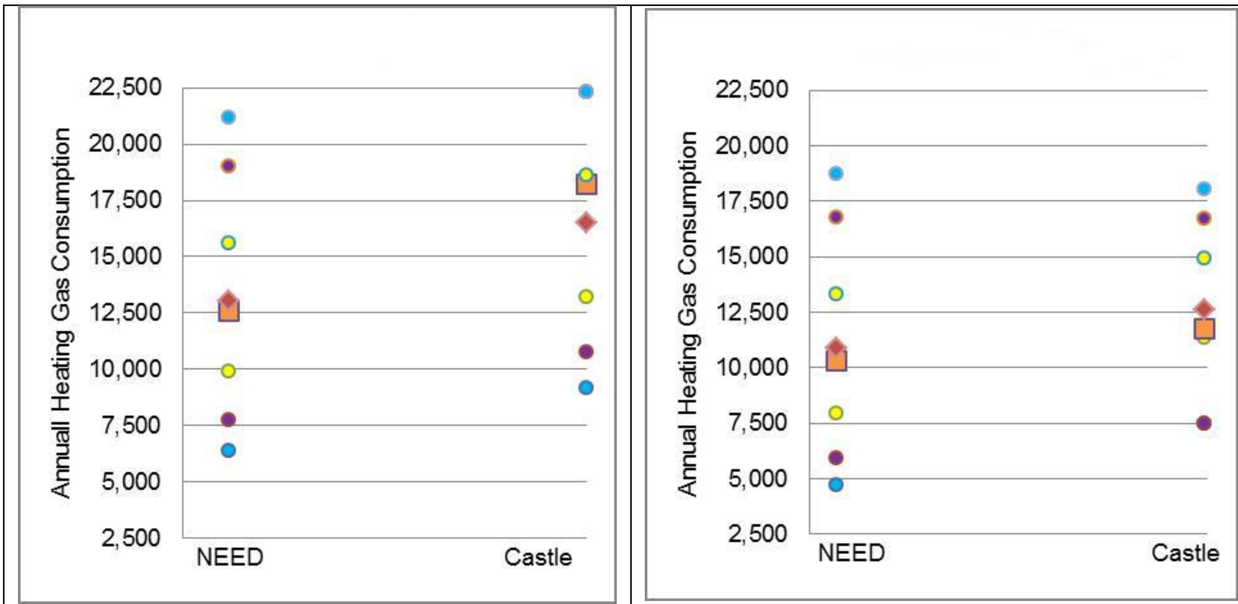


Figure 5 *Skew distribution legend*

Figure 6 shows the skewed distributions in NEED on the left and NCRF on the right for two bungalow samples. Figure 6 shows a decrease in heating gas consumption (in kWh) as the floor area becomes smaller for both NEED and NCRM. However, the annual Energy Consumption (use) Intensity (density) (AECI) is a preferred term for benchmarking the comparative energy use of Buildings [60] that are different sizes, and which, therefore, perform better. The AECI can be used for comparing individual energy end-uses, as well as total energy use. The AECI is an appealing metric for energy efficiency measures as declines in energy intensity are a proxy for efficiency improvements provided energy intensity is represented at an appropriate level of disaggregation (buildings) to provide meaningful interpretation. AECI is calculated by dividing the total energy consumed by the building in one year (measured in kWh) by its total footprint area [61].

NEED is a framework for combining data from existing sources: Meter point electricity and gas consumption data, Valuation Office Agency (VOA) property attribute data, the Homes Energy Efficiency Database (HEED) containing data on energy efficiency measures installed, and data modelled by Experian on household characteristics. However, for example, the consumption data is based on billing data are sometimes estimated, the gas and electricity years do not cover calendar year – or the same period as each other, HEED data only covers measures installed through Government schemes; no information on measures installed by households themselves or installed when the property is built, and includes more properties with a higher turnover of occupants – properties that have been sold recently and properties which are rented [62, 63]. The tables show that NEED data is skewed [54] as the mean is not equal to the median. In these cases, the median is generally considered to be the best representative of the central location of the data in the sample. Also, the NCRF heating gas estimate does not have the same skewed distribution that NEED data has, as shown in the columns (mean and median difference) giving a strong argument that the local area characteristics matter in micro-planning more than regional averages.



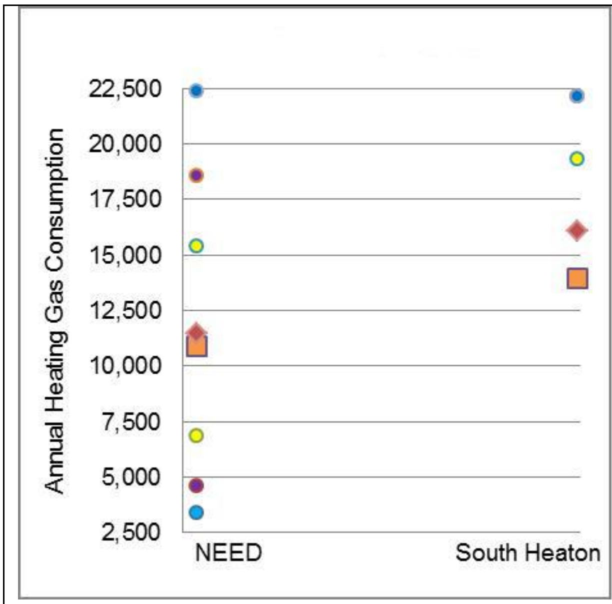
Sample 1: Castle Bungalow, PA = 1965-1982, FA = 76 to 100sqm

Sample 2: Castle Bungalow, PA = 1945-1964, FA = 50 to 75sqm.

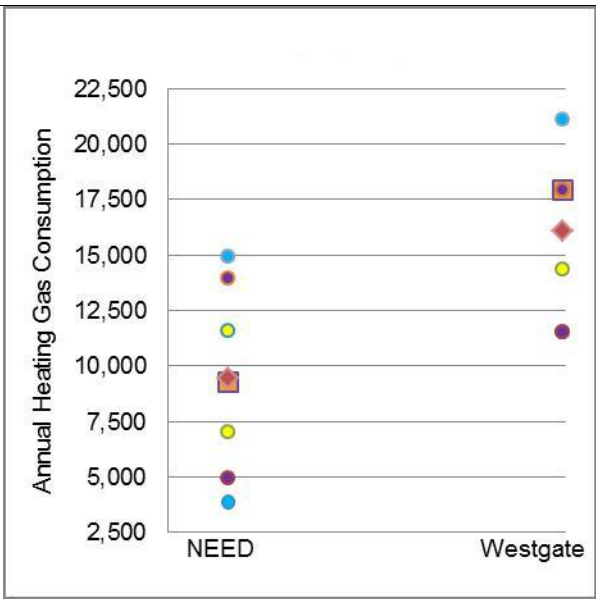
Figure 6 Skewed distributions for NCRF and NEED bungalow samples

Figure 6 shows that in Castle the mean and median NCRF annual heating gas consumption are higher than the NEED values. This suggests again that the model results are dependent of the data set composition in the NCRM samples, which are basically individual houses in the area that have a low efficiency i.e. that local area characteristics play an important part in the sample's energy efficiency. In the NCRM data set, the bungalows in Castle (in these samples) are mostly uninsulated and using standard and combi boilers.

Figure 7 shows the skewed distributions of the annual energy use (kWh) in NEED on the left and NCRF on the right for end-terraced properties. Figure 7 shows that there are a high number of low efficiency dwellings, i.e. local area characteristics play an important part in the efficiency of the dwellings that make-up the sample. In South Heaton, in general, properties have uninsulated solid walls.



Sample 3: South Heaton End-terraced, PA = Pre 1919,
FA = 50 to 75sqm



Sample 4: Westgate End-terraced, PA = 1965-1982,
FA = 50 to 75sqm

Figure 7 Skewed distributions for NCRF and NEED end-terraced samples

There is a cautious results in the comparison with NEED data because of two reasons: first, the NEED sample composition is not known whereas the NCRM sample is a collection of known properties, and second, the NEED data set disaggregates gas heating consumption by three variables: dwelling type; dwelling age; and floor area and this study utilises ten variables to produce disaggregated results.

Under our framework, retrofit programmes could be possible designed differently to account for the needs of different sectors and for different dwelling types, levels of insulation, heating system and other features, i.e. the NCRF data set composition in Westgate suggests interesting measures in the heating provision, e.g. the number of properties on electric provision of heat is 41% in Westgate LLSOA 8440, and 76% in Westgate LLSOA 8397. A likely measure is to change the provision to heat pumps and/or CHP, as this can improve the efficiency in the housing stock in selected areas and in turn will reduce the energy consumption in the area. Similarly, the NCRM data set composition in South Heaton suggest appropriate measures for reducing the energy demand. The local area characteristics leads interesting measures in the building envelope, e.g. the proportion of insulated (i) to total (t) solid wall properties in the complete city sample equals i/t=258/7,654=0.033, in South Heaton sample equals i/t=12/1010=0.012 and in the Westgate sample equals i/t=18/292=0.062, i.e. only 1.2 percent of the Late Victorian/Edwardian terraces from 1870-1914, with solid walls in South Heaton being insulated and thus solid wall insulation retrofit measures may have a potentially large impact in South Heaton.

We argue that the microclimate is likely to have affected the Castle results due to vegetation, which in urban areas plays a significant role in regulating the urban climate. It is an effective measure to create an "oasis effect'" and mitigate urban warming at micro levels. Additionally, when vegetation is arranged throughout a city in the form of urban parks, the energy balance of the whole city can be modified through adding more evaporating surfaces by providing sources of moisture for evapotranspiration and more absorbed radiation can be dissipated in the form of latent heat rather than sensible heat [64]. Urban parks can extend the positive effects to the surrounding built environment.

Yu and Hien [64] argue that there are least three ways to study the role of green areas in moderating an urban climate: (i) studies focused on surface temperature through the use of airborne or satellite thermal infrared remote sensors in, for example, the work of Yuan and Bauer [65], (ii) studies focused on in-depth field measurements at micro-level, and (iii) studies focused on numerical calculation to predict the thermal benefits of green areas in cities. This study uses the thermal infrared remote sensing method because the Newcastle City Council (NCC) has a thermal image available.

Planning regulations have an impact on the physical characteristics of urban landscapes [66], by imposing such restrictions as maximum building height, density, and land use types. These in turn, control surface energy exchange, weather and climate systems, and other environmental processes. Weng and Schubring [67] demonstrate that land surface temperature possessed a slightly stronger negative correlation with the unmixed vegetation fraction than with normalized difference vegetation index for all land cover types across the spatial resolution (30 to 960 m). Additionally, vegetation distribution, intensity, continuity etc. play crucial role for regulating land surface temperature over space

The thermal image was taken on Tuesday 2nd and Wednesday 3rd March 2010, between 7pm to 11pm (those days were cold, dry and clear and people were most likely to be heating their homes). This image was then colour coded and the outline of buildings laid over the data. The colour code provides a heat loss profile for every building in the city. The rating and hence the colour on the map will be affected by a number of factors, such as: (i) whether the heating was turned on at the time the images were taken, (ii) how much heating was being used at the time (affected by the household composition) and whether there is a heating control in the dwelling, (iii) the type of building and building material used in its construction, (iv) whether the loft space had been converted for use as an additional room, (v) how much insulation there is in the property, especially in any loft space. At the end of the process, all domestic properties in Newcastle have been given a heat loss parameter of between 1 (low heat loss) to 5 (high heat loss) [68].

The neighbourhood chosen for the microclimate quantification is Kingston Metro (Castle LLSOA 8294). Kingston Metro is a very uniform area, with almost 50% of standard semi-detached houses and semi-detached type housing in multiples of 4, 6, 8, and so on. These houses correspond to the 1964–1979 period. The LLSOA has a plot ratio equal to 0.3, see Figure 8.

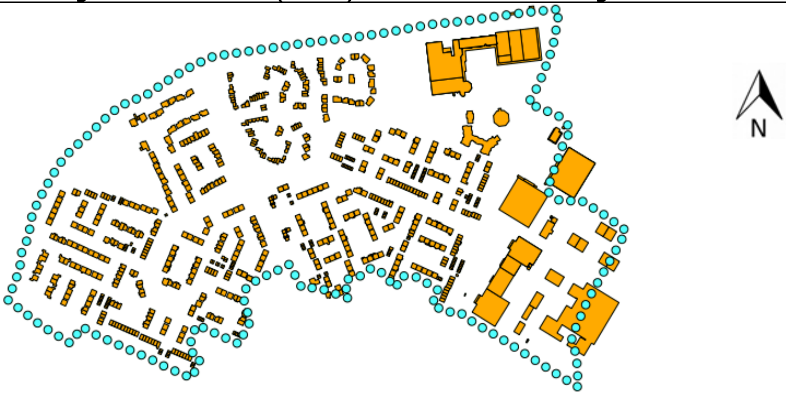
Temperature variation is detected within a single land use land cover unit [69]. Note that, Castle urbanization (see Figure 8a) is the main driving process of land cover changes and consequently rise of land surface temperature (see Figure 8d) in uniform areas (see Figure 8b) These might be a second use of the thermal images in aggregated buildings in sub-city areas, beside the leaks and insulation failure in a building envelope in individual buildings.

Figures 8c and 8d show the Castle LLSOA 8294 heat loss profile of the south of Kingston Park Metro. Figure 8a is a mosaic and colour corrected data as a base map service colour from google map; Figure 8b are the corresponding OS MasterMap™ building outlines; finally, Figures 8c and 8d are the standard deviation and the average mean choropleth maps derived from the thermal image. All choropleth maps are presented with the values being placed in one of five bins shown using sequential colour ramps. Our strategy to split out each measure into the five bins is determined automatically using the quantile algorithm [70], based solely on the percentage average of the measure across the currently used statistical unit of the temperature distribution, i.e. based on where the pixel falls in the histogram, into an integer between 1 and 5, with 1 representing being the "coolest" pixels and 5 being the "hottest", and the standard deviation of this average (see map 8d). This strategy did not use the maximum or minimum values, so it is possible for some measures of temperature distribution fall into one or more of the outlier bins. Each spatial statistical unit is coloured according to the proportion that has a particular temperature distribution. The 8c map represents the standard deviation. The standard deviation is a statistical technique type of map based on how much the data differs from the mean. Then, each standard deviation becomes a class in our choropleth map. Despite its inconsistencies, standard deviation types of maps might be one of the most appropriate because of its statistical origin.

In the LLSOA 8294, almost 50% of the housing stock is standard semi-detached houses and semi-detached type house in multiples of 4, 6, 8, etc. These houses correspond to the 1964-1979 period. The second urban form variable is density/mixing of land use and built form. This study argues that the urban density, defined as number of dwelling per hectare, is not a valid proxy for energy use.

The street layout determines the building orientations. This is shown particularly in the Castle neighbourhood in Figure 8 map a. The resulting building orientation affects the energy use for heating and electricity depending on window area distributions and shading from neighbouring buildings. The neighbouring buildings in the urban context reduce solar radiation and daylight availability to individual buildings.

a. Image of Newcastle (2013) retrieved from Google Earth™



b. OS MasterMap™ building outlines

c. The standard deviation of the classes in the buildings

d. The average class (mean) recorded in the buildings

Figure 8 Heat loss profile for every building in Castle LLSOA 8294

(a) Dominant patches areas (82, 84 & 86)

(b) Annual Gas intensity consumption (kWh/year/m^2)

(c) Annual electricity intensity consumption (kWh/year/m^2)

(d) Annual energy intensity consumption (kWh/year/m^2)

Figure 9 Building types for Castle LLSOA 8294 at scale 1:3,500

In Figure 9, map (a) represents a land cover raster image from Google Earth™, map (b) represents the OS MasterMap™ vector building outlines, map (c) represents the standard deviation of the classes in the buildings, and map (d) represents the average class (mean) recorded in the building. Map (d) shows a significant number of buildings in green (the likely class for the mean is 2) in the outer North West, where the vegetation is surrounding the buildings. The same type building then progressively turn to yellow (the likely class for the mean is 3) toward the centre of the image denoting that perhaps the inter-building effect (IBE) (Inter-building effect: Simulating the impact of a network of buildings on the accuracy of building energy performance predictions) is more noticeable than the vegetation and possibly can impact the accuracy of building energy simulation predictions. Pisello et al. [71] argue that IBE is much more dependent on the specific configuration of the urban environment considered in terms of shape, orientation, opening percentage, and building features in general rather than on climate variability. As a conclusion, this paper argues that the limitations of traditional energy assessment methods can be spanned and innovative strategies can be proposed for energy efficiency improvements using remote sensors

5. Discussion

Most physical energy models in the United Kingdom do not take into account the surface temperature; however, at the scale of the individual buildings detailed models exist, such as EnergyPlus™. Urban microclimate effects on energy demand were analysed by Yang et al. [72], who used an urban microclimate model and the building energy software EnergyPlus™ [73]. These models have to be supplied with suitable boundary conditions, which represent the urban microclimate. However, for this study, in order to consider interactions between energy demand, surface temperature, vegetation and the local urban microclimate, more complex tools are needed. The interactions between buildings and the landscape in low density Castle presumably create a real increase in energy use because there is an increase in the mean daily heat output from the heating system due to smaller increases in the outdoor air temperature due to heat island effects. One possible way to improve the weather data would be to spatially merge local area-based data with detailed weather data that is readily available. Urban microclimate is a key element during the design stages of sustainable and comfortable urban spaces, although the physics underlying the interaction of urban microclimate with buildings is complex to model.

Our energy estimation results do not consider the inter-building effect created by surrounding buildings. The energy use is underestimated in aggregated buildings because of the reduced solar radiance. However, this effect is complex and requires the modelling of a network of buildings. The Castle case study shows that the LLSOAs energy use may have modelling inaccuracies created by the nearby buildings. Physical building models would need detailed topological information (as provided by NCRM) in order to model inter-building effects effectively. For densifying urban environments, this is likely to be a relatively significant effect. Specifically, the role of inter-building effects must be examined as a number of researchers have suggested (e.g. Pisello et al. [74], Bueno et al. [75] , Yang et al. [72]). Also, urban form from the point of view of environmental performance in cities as addressed in Adolphe [76]; and, energy use and density as the results of Steemers [77] seem to suggest.

Finally, the cluster energy method is a process that suggests that the cluster size and composition not only reflect the energy efficiency of the Newcastle stock, but what was encouraging, the potential impact of applying certain retrofitting measures is possible. What was good from the cluster model district results is that they enable us to model aggregate energy use using a reduced number of variables. Also, in cities the scale problem arises when spatial data are aggregated into successively larger areal units. The detailed micro-simulation used for predicting the heating needs of a given building has limitations when taking into consideration the surroundings of a particular building. Indeed, shadowing and heat exchange in cities are non-negligible and ask for a broader scene description in the urban context. This problem is more important in heterogeneous than homogeneous study areas. On the other hand, broadening the modelling scale also opens opportunities to capture other aspects of urban energy use, such as energy distribution networks and shared use of power plants.

6. Conclusion

This study has described the spatial variability for sub-city areas in UK cities, with Newcastle upon Tyne as a case study. The energy modelling approach is bottom-up in neighbourhoods and communities. Three districts were studied, Castle, South Heaton and Westgate. The annual energy use (electricity and gas) was estimated using the year 2009 as a base scenario. The spatially enabled input database included four main data sets: two local data sets (NCRM WarmZone and NCRM Gazetteer) and two national data sets (English Housing Survey and Ordnance Survey) and a thermal image. The energy model used to estimate the energy end-use was the Cambridge Housing Model (CHM). CHM is a national model requiring a full SAP input.

This study has shown that the energy use results in the sub-city energy model are affected by local area characteristics in all the case studies. In some cases, these characteristics result in different building types having similar energy use, which suggests care must be taken when considering NEED regional mean characteristics from property type alone as a substitute for energy use. On the quality of NEED data, DECC argues that the evidence base (from field trials of certain measures and NEED) of the "in-situ performance" of the full range of eligible measures in Green Deal is patchy

Therefore that evidence is adjusted by the introduction of other factors. The "in-use" factors potentially alter the amount of finance that can be offered to consumers per measure and the confidence in the savings on which the Golden Rule is based, i.e. the expected financial savings must be equal to or greater than the costs attached to the energy bill. We argue that thermal images has several uses in this evidence based approach, first in identifying leaks and insulation failures in a building in per-building base, and second, that vegetation distribution, intensity, continuity etc. regulate land surface temperature over the built environment in aggregated buildings in sub-city areas Finally, the modelling of the physical processes in individual dwellings with spatial components has potential to provide LAs with realistic, simulated estimated energy values for buildings that can be aggregated at many scales to provide a baseline for use in retrofit or micro-generation or other energy related planning.

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